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How managers can deal with complex issues: a semi-quantitative analysis method of causal loop diagrams based on matrices

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HOW MANAGERS CAN DEAL WITH COMPLEX ISSUES: A SEMI-QUANTITATIVE ANALYSIS METHOD OF CAUSAL LOOP DIAGRAMS BASED ON MATRICES

ABSTRACT

The increasing complexity of the modern world creates both higher risks and new interdependencies in the socioeconomic environment. To cope with these challenges powerful new tools must be applied to find sustainable solutions. System dynamics is a field that offers potential assistance in dealing with complex issues. However, managers and politicians often lack the knowledge and necessary skills to apply quantitative methods in their decision-making process. In contrast, qualitative approaches are easily understood and handled but have limited capacities for analysis. To address this gap, we have developed a bundle of tools tailored for managers and politicians facing complex problems. These tools enable executives to recognize effective levers and assess potential consequences of specific interventions in a highly interconnected system. The approach detailed here equips decision makers with a powerful method to develop, test, and communicate strategies to find long-term sustainable solutions for complex issues in business and society.

KEYWORDS

Causal loop diagram, semi-quantitative approach, adjacency matrix, feedback, mental model, strategic decision making

INTRODUCTION

The growing complexity of our environment caused by the globalization of stakeholders, institutions, infrastructure and organizational processes has led to new dependencies and unexpected feedback processes. This complexity results not only from rapid technological and economic changes, but also from increasing interdependencies in a globalized society. The global economy has never been so interconnected as it is today, which was clearly demonstrated by the worldwide economic and financial crises initiated by the US housing bubble in 2006 (Amann et al., 2011). Consequently, the complexity of the problems that managers and policy makers must address grows quickly over time and is greater now than it has ever been. To cope with this challenge, quantitative or qualitative models from system theory can be used which allow decision makers to model complex linkages of stakeholders, institutions or processes in an easily understandable way (Senge, 1990).

Maani and Cavana (2000, p. 135) define system theory as "the ability to see things as a whole. It combines the art of seeing interconnections and the science of explaining complexity." System theory is based on the theories of Bertalanffy (1969) and Rapoport (1986), involving two powerful streams: system dynamics and organizational cybernetics. Both concepts aim to design and control sustainable organizations and social systems in general (Schwaninger et al., 2008), and have influenced management and organizational theory, education and practice (Ulrich, 1984 and 2001; Espejo et al., 1996; Jackson, 2000; Schwaninger, 2001 and 2009). Overall, system theory has contributed to a better understanding of complex systems and has provided powerful tools for solving complex problems, not only in management but also in many other fields (Bar-Yam, 1997; François, 1999).

This research contributes to the qualitative stream of system dynamics, targeting decision makers from business and politics.[1] System dynamics (SD) was elaborated to a large extent by Jay Forrester at MIT, and delivers a methodology for understanding complex systems' behavior and their underlying structures (Forrester, 1961; Richard-

[1] For the purpose of this paper, we refer to the term qualitative system dynamics to indicate the use of non-simulation based system dynamics. We consider qualitative SD as a set of methods consisting of causal loop as well as stock and flow diagrams.

son, 1991).[2] Although SD was often perceived and applied as a quantitative simulation approach, SD incorporates both qualitative and quantitative methods (Wolstenholme, 1982 and 1999). There is a notable debate regarding the utility of qualitative modeling in the SD community. Sterman (1994, p. 321) reflects on the limits of qualitative maps, saying that they are “simply too ambiguous and too difficult to simulate mentally to provide much useful information on the adequacy of the model structure or guidance about the future development of the system or the effects of policies.” Coyle (2000) defends the qualitative modeling approach and shows that it can have policy relevance. In certain circumstances, quantification is problematic. For example, if the modeler intends to include “soft” variables, which are often indispensable to build a realistic model. For these soft variables, the modeler must make assumptions that can bring substantial uncertainty into the model (Coyle, 2000, p. 227). In this case, quantified modeling is not a priori better than qualitative analysis. In the absence of quantitative data, causal loop diagrams (CLDs) or stock and flow diagrams (SFDs)—both qualitative mapping tools—offer a promising option to visualize complex problems (Wolstenholme et al., 1983). We believe that qualitative system dynamics has relevance and benefit for the SD community if applied in an appropriate context. This can be a setting where many influencing factors are soft and thus difficult to quantify, or a situation where time and resources are too scarce to construct a formal model based on mathematical equations. Richardson (1996, p. 8) states in his paper on future problems of SD that the field has not yet determined “when to map and when to model.” Both approaches—quantitative and qualitative—enable users to externalize and communicate their assumptions by sharing their mental models (Doyle et al., 1998).

Compared to quantitative methods, qualitative methods are easier to understand and are therefore more suitable for managers or decision makers in policy (Dhawan et al., 2011). To date, however, the possibilities for analyzing CLDs or SFDs without mathematically defining the relationships between the variables are limited. We aim to go further than pure qualitative analysis of diagrams and integrate a certain level of quantification. Van Zijderveld (2007) developed a semi-qualitative tool called

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[2] Forrester’s guiding idea was to simulate complex, nonlinear, multi-loop feedback systems. Therefore, he integrated essential thoughts and techniques from three different emerging disciplines: control engineering, cybernetics and organizational theory (see for example Meadows (1980, p. 20)).

MARVEL (Method to Analyze Relations between Variables using Enriched Loops) to model system behavior and conduct policy analysis. However, his tool is rather complex and not very user-friendly.[3] Our goal was to develop a well-structured and easily applicable tool which is able to support managers and politicians facing complex problems. This tool has been tested and refined with managers from various industries in our executive education program for several years. Findings indicate that this approach helps the executives to think holistically about challenging business or social problems. In addition, it is an excellent communication tool which allows managers to discuss a problem thoroughly with peers. In this paper we will present the methodology behind this tool.

Analytical method

In this article, we present a method to analyze CLDs or SFDs in a dynamic and highly interconnected environment. The approach detailed here is primarily based on two adjacency matrices. As Oliva (2004, p. 315) states in his article, "the structure of a system dynamics model can be represented as a digraph (CLD), where the variables are the vertices and the edges are the relationship 'is used in' […]. To facilitate computations, a digraph is often represented as an adjacency matrix." The starting point of this analysis is a CLD (directed graph) or SFD that must first be converted to a CLD. Next, two adjacency matrices are built, indicating impact and time delay for each edge (relationship). "Time delay" means the time needed for an impulse to travel from vertex (variable) x to vertex (variable) y. In the next step, a shortest path finder algorithm is applied to calculate the smallest delay and the corresponding impact between any connected variable pair in our model. Finally, we analyze the feedback cycles of the model and its robustness, which is done through variable removal.

Perspectives and Matrices

Following the basic concepts of system theory, we focus on both the interactions between a variable and the system as a whole, and the interactions between a variable pair in a certain system. Additionally, feedback cycles and system implications of

[3] Van Zijderveld established 24 information elements that need to be defined before one can analyze a CLD.

variable deletion are of interest. Therefore this method uses three perspectives to address complex issues using several matrices as represented in Table 1.

Table 1: The three perspectives of this analysis method

<table>
<tr><th>Matrix</th><th>Matrix description</th><th>Function</th></tr>
<tr><td colspan="3">First perspective: Relationship between a variable and the system as a whole</td></tr>
<tr><td>Cross-Impact Matrix (CIM)</td><td>Indicates the impact of each variable</td><td rowspan="2">Identification of intervention and indicator variables</td></tr>
<tr><td>Cross-Time Matrix (CTM)</td><td>Indicates the temporal influence of each variable</td></tr>
<tr><td colspan="3">Second perspective: Relationship between two variables in a system</td></tr>
<tr><td>Cross-Delay Matrix (CDM)</td><td>Indicates the shortest path with respect to time for each variable pair</td><td rowspan="2">Evaluation of different policies</td></tr>
<tr><td>Cross-Effect Matrix (CEM)</td><td>Indicates the first effect for each variable pair</td></tr>
<tr><td colspan="3">Third perspective: Feedback structure</td></tr>
<tr><td colspan="3">No new matrix needs to be introduced</td></tr>
</table>

In the first section of this paper, a method that captures the relationships between a variable and the system is presented. For the purpose of this analysis, we begin with a Cross-Impact Matrix (CIM) drawn from literature (Vester et al., 1980) and derived from a causal loop diagram. Further, we introduce a Cross-Time Matrix (CTM) to address the time dimension. The CTM is constructed similarly to the CIM and can be easily completed by decision makers. Combining CIM and CTM into two simple portfolios helps to define the different roles that can be attributed to the individual variables. We categorize variables according to their degree of influence on the system or the degree to which the system influences them. In addition, we distinguish between variables with high or low impulse permeability. A variable with high impulse permeability receives and transmits impulses with greater average speed as compared to one with low impulse permeability. This will be discussed later in greater detail.

The above discussion of the first perspective of this analysis method has addressed the following research questions:

- What variables are most influential in this CLD and hence appropriate for intervention in the system?
- Which variables are best suited to measure changes in this system (indicators)?

In this section on the second perspective, relations between each variable and all of the other variables in the system are examined. To do this, it is important to know how long it takes for an impulse to reach variable y starting from variable x or how long it takes for an intervention to produce a measurable change. To answer these questions, the temporal relations between two variables and the impact over a certain time span are calculated using an adapted version of the Floyd-Warshall algorithm applied to the CTM and the CIM.

In this section, we will concentrate on the following research questions:

- How long does it take until an intervention in the system produces a detectable change in the indicator variable?
- How big is the first effect in the indicator variable after an intervention?

In the final section, we analyze the feedback cycles of the model. To do this, we take a closer look at the composition of reinforcing and balancing loops, and conduct a CLD robustness analysis by studying the effects in terms of feedback structure if single variables are removed from the system.

These are the research questions addressed by this analysis:

- What does the feedback structure look like in this CLD?
- What are the consequences for CLD robustness if single variables are deleted?

RELATIONSHIP BETWEEN A VARIABLE AND THE SYSTEM

To analyze the relationship between a variable and the system, the following two matrices are introduced and must be completed by decision makers: a CIM for impact, following the approaches of Vester (2002) as well as Gomez and Probst (1999), and a Cross-Time Matrix (CTM) for the time dimension.

The Cross-Impact Matrix (CIM)

The CIM is a method of describing the influence of each variable with respect to the system. In contrast to Gomez and Probst (1999) and Vester (2002) where all direct and indirect impacts are valued, we suggest that only the direct links are taken into account. This will enhance the quality of data and information gathered.[4]

To illustrate how this method works, we present a didactic example that provides an understanding of the modeling and calculation process discussed. The example is a simple system that describes the dynamic of a population (adapted from Sterman, 2000). It is shown as an SFD in Figure 1 and explained in more detail in Appendix A.

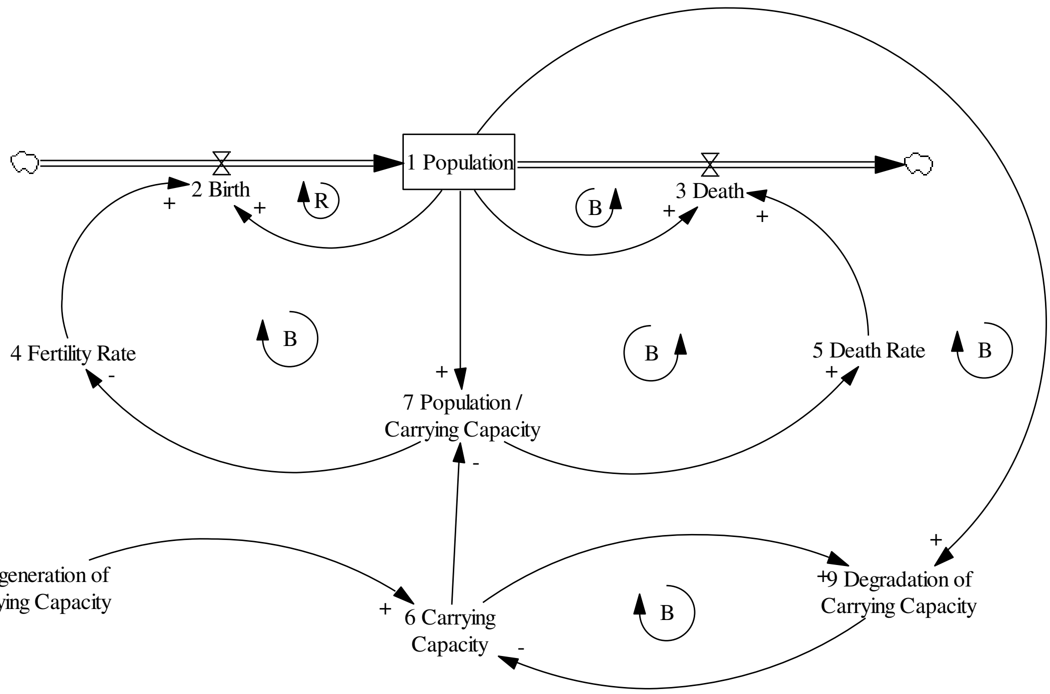

Figure 1: Population growth model (SFD)

For convenience and easier handling of the adjacency matrices, we transform the SFD into a directed graph or causal loop diagram (see Figure 2).

[4] We have found through experience in our executive education program that decision makers have major difficulties in providing reliable information on the indirect impacts of variables.

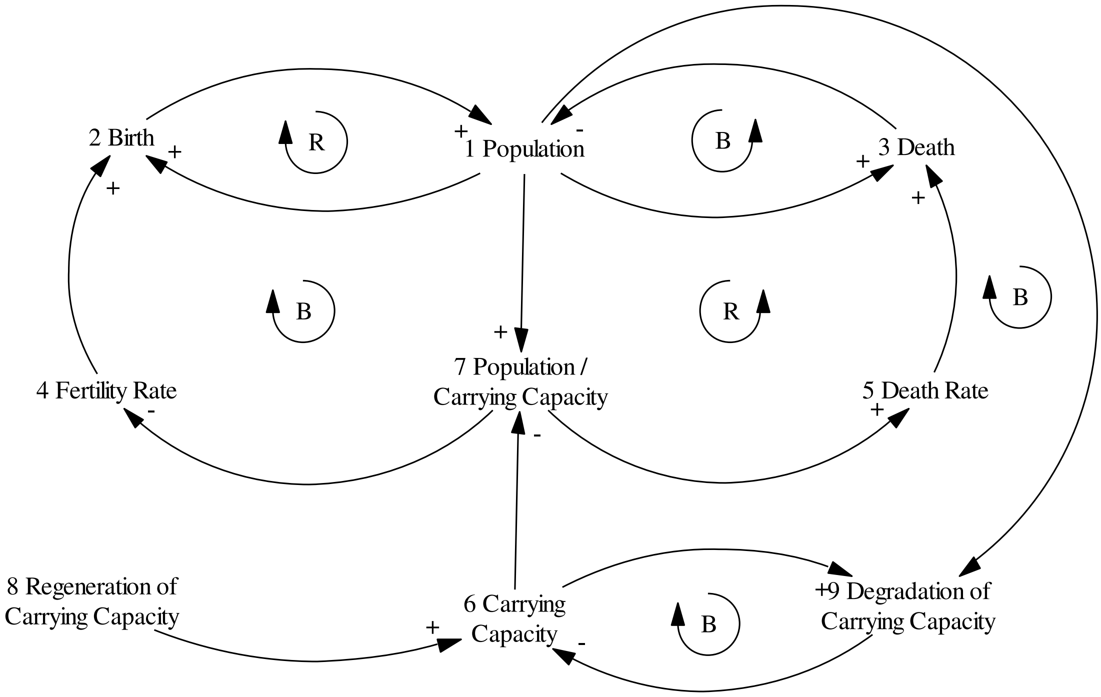

Figure 2: Population growth model (CLD)

Once a CLD is constructed, the relative weight of each identified edge must be specified. For example, if we look at the causal link between variables 8 (Regeneration of Carrying Capacity) and 6 (Carrying Capacity), we have to answer the following question: if Regeneration of Carrying Capacity increases, will this lead to a proportional increase in Carrying Capacity? Using the code in Table 2, the impact strength between connected variables can be defined.[5] In addition, it is important to pay attention to the link polarity and adjust the sign of the code accordingly. Relative weights of every edge in this population growth model are displayed in an adjacency matrix, the Cross-Impact Matrix (see Table 3). For a better understanding of Table 3, assume that variable x is Regeneration of Carrying Capacity and variable y is Carrying Capacity.

[5] The data applied in the matrices are only for didactic purposes and have not been submitted to experts for approval. We suggest using 2/3 for a sub-proportional and 3/2 for an over-proportional reaction to make the calculations simple. Because 2/3 is the inversion of 3/2, proportionality is achieved when the two factors are multiplied together. For the CIM in Table 3 multiplication is not necessary, however, to calculate the effects of two consecutive links in the next section, multiplication will be required.

Table 2: Codes used to describe the impact between variables x and y

empty	no influence: there is no direct link between variables x and y
$\frac{2}{3}$	Sub-proportional: variable y reacts weakly to a change in variable x
1	Proportional: variable y reacts similarly to variable x
$\frac{3}{2}$	Over-proportional: variable y reacts strongly to a change in variable x

Table 3: Cross-Impact Matrix for the example 'Population Growth'[6]

impact from	**to**	1	2	3	4	5	6	7	8	9	**AS**
1	Population		0.67	0.67				1.00		0.67	**3.00**
2	Birth	1.00									**1.00**
3	Death	-1.00									**1.00**
4	Fertility rate		0.67								**0.67**
5	Death rate			0.67							**0.67**
6	Carrying capacity							-1.00		0.67	**1.67**
7	Pop rel. to Cc				-1.50	0.67					**2.17**
8	Regeneration of Cc						0.67				**0.67**
9	Degradation of Cc						-1.50				**1.50**
PS		**2.00**	**1.33**	**1.33**	**1.50**	**0.67**	**2.17**	**2.00**	**n.d.**	**1.33**	

The active sum (AS) is the sum of all direct influences (outgoing flows) that can be attributed to a certain variable. It is the sum of the values in the row of a single variable and indicates how strongly this variable affects or dominates the system. The passive sum (PS) is the sum of all of the incoming flows, and indicates how strongly a variable is affected or dominated by the system. To calculate the incoming and outgoing flows, only absolute values are taken into account because only the variables' overall activity—calculated as active sum—or passivity—calculated as passive sum are of

[6] n.d. stands for not defined. As Table 3 shows, variable 8 (Regeneration of Carrying Capacity) has only an active sum value. Variable 8 is a so-called "outside variable" because it influences the system from outside. It is connected to only one variable and thus does not show a high degree of cross-linking within the sample system.

interest. Therefore, the link polarities are not taken into account when calculating the AS and PS.

The Cross-Time Matrix (CTM)

Time plays an important role when dealing with complex problems. Therefore, the discussion focuses on how quickly an impact is spread from one variable to the next. We suggest constructing a Cross-Time Matrix (CTM) similarly to the Cross-Impact Matrix (CIM), where the time delay of two consecutive variables must be indicated. As in the CIM, we analyze only direct relations. To assess time delays, the code presented in Table 4 is applied. To avoid bias, time categories must be associated with real numbers and coded proportionally. It should be noted that, depending on the system, time categories could refer to different time frames.

Table 4: Codes used to indicate the time delay between variables x and y

empty	no influence: there is no direct link between variables x and y
1	Immediately (within one year): variable y reacts immediately to changes in variable x
2	Short-term (2 years): variable y reacts with a short time delay to changes in variable x
5	Middle-term (5 years): variable y reacts with a moderate time delay to changes in variable x
10	Long-term (10 years): variable y reacts with a long time delay to changes in variable x

Table 5: Cross-Time Matrix

time from / to		1	2	3	4	5	6	7	8	9	PD
1	Population		5	10				2		5	**5.50**
2	Birth	1									**1.00**
3	Death	1									**1.00**
4	Fertility rate		2								**2.00**
5	Death rate			2							**2.00**
6	Carrying capacity							2		10	**6.00**
7	Pop rel. to Cc				5	10					**7.50**
8	Regeneration of Cc						10				**10.00**
9	Degradation of Cc						5				**5.00**
RD		**1.00**	**3.50**	**6.00**	**5.00**	**10.00**	**7.50**	**2.00**	**n.d.**	**7.50**	

Instead of AS and PS, in the CTM we use produced delay (PD) and received delay (RD) to characterize variables in the context of time. PD indicates how much delay is caused by a certain variable. For example, a variable with a high PD-value transmits stimuli slowly through its outgoing links. Similarly, RD indicates whether a variable shows a slow or a quick reaction to changes in the system (on average). Hence, a variable with a high RD-value receives impulses slowly through its incoming links. In contrast to the CIM where the AS and PS are calculated by summing up the strengths of the impacts, it makes no sense to sum up all of the delays in the CTM as delay here only depends on whether the delays are short-term, middle-term or long-term. Instead, we use the arithmetic mean of the delay, which is less dispersed. Thus, the average PD and RD for each variable are defined as follows:

$$\mathrm{PD_i} = \frac{\sum_{j=1}^{n} \mathrm{ctm(i.j)}}{\mathrm{n}}, \text{ respectively } RD_j = \frac{\sum_{i=1}^{n} ctm(i.j)}{n},$$

where n corresponds to the number of involved nodes.

Earlier the term impulse permeability (IP) was introduced as a measure of the resistance of a variable to transmitting systemic impulses, similar to the electrical concept of resistance. This can be used to categorize variables with incoming and outgoing links according to impulse transmission time. Impulse permeability is inversely proportional to the sum of PD and RD.

$$IP_i \sim 1 / (RD_i + PD_i)$$

In the following we will use PD to determine variables appropriate for intervention and RD to recognize indicator variables.

Combining the Cross-Impact and Cross-Time Matrices

The combination of time and impact dimensions is important for decision makers in deciding which variables can be used for intervention and which as indicators. To aggregate impact and time and to broaden analysis, we connect the CIM with the CTM. We use two simple portfolios, first the active sum (AS) together with the produced delay (PD) in order to identify variables suited for intervention, and second the passive sum (PS) together with the received delay (RD) for detection of indicator variables.

1. Variables Suited for Intervention

An ideal intervention variable should be capable of changing the system substantially. This means that a high number of outgoing links is a prerequisite for an efficient steering variable. Additionally one must determine if a change originating from an intervention needs to spread slowly or quickly through the system. For this purpose, it is best to combine the active sum and the produced delay in a portfolio.

The portfolio in Figure 3 is derived by the AS from the CIM and the PD from the CTM, then divided into four quadrants for simple categorization of the variables. We used the medians of PD and AS to set the boundaries for the quadrants. A precise description of the four quadrants and the corresponding variables is given in Table 6. Reasonable intervention variables can be found in quadrant I if a change needs to “diffuse” quickly in a system, or in quadrant II if one intends to make a slower change. Both types of variables (from quadrant I and II) are suited for intervention because they exert a large influence on the system. As can be seen in Figure 3, variables 1 (Population), 6 (Carrying Capacity) and 7 (Population relative to Carrying Capacity), completely in quadrant II, and variable 9, (Degradation of Carrying Capacity) on the split line between quadrant I and II, are potential candidates for intervention.

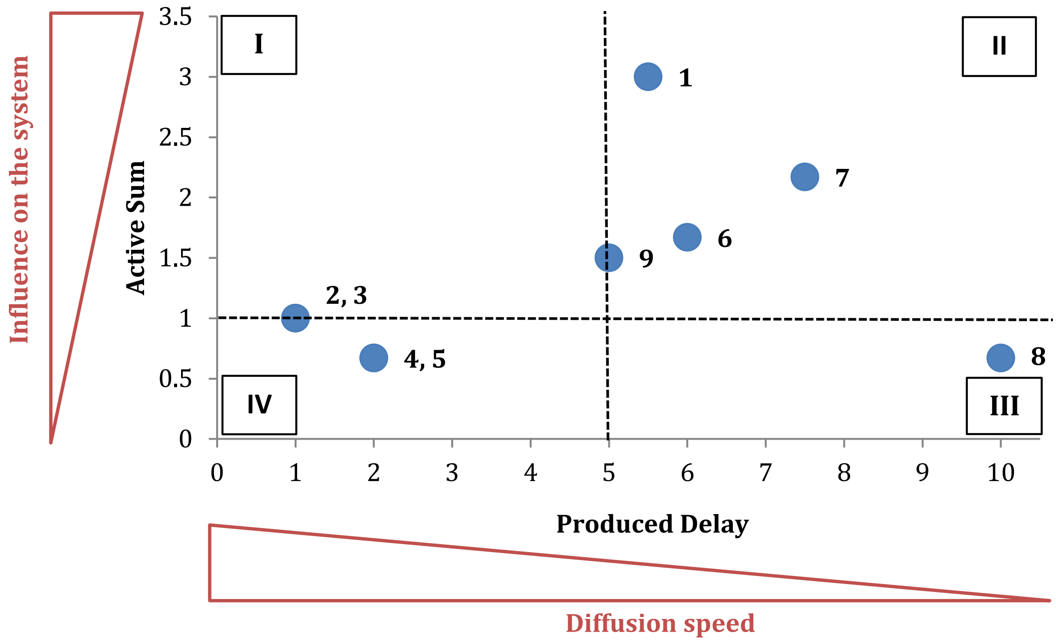

Figure 3: Best intervention variables: combining AS and PD

Table 6: Categorization of variables according to their utility as intervention variables

I	High AS value and a low PD value High impact and react very quickly to changes Best suited for interventions within a system
II	High AS and PD values High impact but rather long paths or slow spreads through the system Appropriate as intervention points, if the goal is a slow but substantial change
III	Low AS value, high PD value No impact and show a delayed reaction Not appropriate for an intervention
IV	Low AS and PD values React quickly to changes, but low impact Not well suited for intervention, because they do not change the system in a meaningful way

Once a decision maker knows which variables are appropriate for intervention, he or she must finally select among the appropriate options the best variable(s). The most appropriate steering variables are those variables that can be directly controlled. With respect to our example, this means that variables 6 (Carrying Capacity, which represents the environment) and 9 (Degradation of Carrying Capacity, which indicates the use of the environment) can be actively controlled by decision makers. Variable 1 (Population) is a stock and can only be regulated by its flows. Variable 7 (Population relative to Carrying Capacity) is not directly manageable either because it is composed of a stock variable (Population). Variables that cannot be directly used as steering variables can often be used as indicators, which will be discussed below.

2. Variables Suited as Indicators

Similar to the combination of the AS and the PD, the passive sum (PS) and the received delay (RD) can be aggregated in a portfolio. Analogous to the preceding section, we can divide the RD/PS-portfolio into four quadrants. An accurate indicator is denoted by a high PS value and a low RD value, whereas a high PS value indicates that the variable is strongly affected by changes within the system. A low RD value means that a variable reacts immediately to changes, or in other words, a low RD value guarantees that a variable "detects" a variation in the system quickly. Consequently, the best indicator variables are located in quadrant I. The features of the other variables in Figure 4 are explained in detail in Table 7.

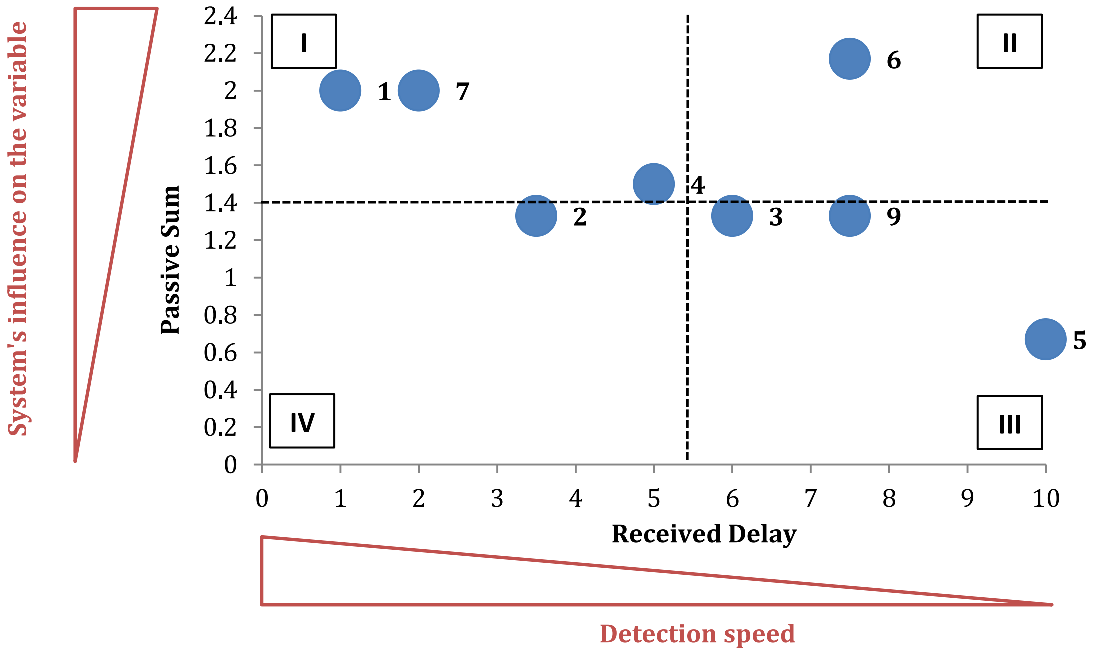

Figure 4: Best indicators: combining PS and RD

Table 7: Categorization of variables according to their utility as indicator variables

I	React intensely and quickly to changes in the system Ideal indicators
II	React strongly but slowly to changes in the system Not suited as indicators
III	React minimally and slowly to changes in the system Not suited as indicators.
IV	React quickly but only moderately to changes in the system Not suited as indicators

Referring to Figure 4, variables 1 (Population), 7 (Population relative to Carrying Capacity), and 4 (Fertility Rate) are the most appropriate for use as indicator variables. All of these variables are affected to a great extent by changes in the system and show a short reaction time to changes. In fact, these variables are important elements of the national statistics used to describe the dynamic of the system “population growth.”

The two portfolios introduced in this section allow us to identify the best intervention possibilities and the best-suited indicators. However, we should bear in mind that a variable must always be interpreted relative to the others. In other words, we must respect the boundaries of the framework in which we are working.[7]

In the next section, we will move our focus to the relationships between a variable pair in order to get more information about different management strategies, their impact, and respective time dimensions.

RELATIONSHIPS BETWEEN TWO VARIABLES IN A SYSTEM

The key questions to be answered in this section are how long it will take for an impulse from variable x to arrive at variable y, and how long it will take until an intervention produces a measurable change in a certain indicator. Information about impact and time span can be very important for strategic interventions. These indicate how long it will take until an investment produces returns. In other words, this procedure should support decision makers in anticipating the efficiency and effectiveness of their intervention measures.

Cross-Delay Matrix (CDM): When does an impulse arrive?

To calculate the necessary time span for an impulse to travel from node x to node y, the established Cross-Time Matrix (see Table 5) can be used.[8] To calculate these time spans, we apply a shortest path finder algorithm, based on the Floyd-Warshall algorithm, to the CTM. A detailed description of the algorithm is given in Appendix B.[9] The results of these calculations, called the Cross-Delay Matrix (CDM), can be seen in Table 8 and are discussed in more detail in Appendix A.

Overall, a CDM provides information about how long it takes until changes in a system are visible. In detail, one can see the minimum delay between a change in a source and a

[7] This follows the closed-boundary concept of Forrester (1969, p. 13) and the "endogenous point of view" concept of Richardson (1991, p. 298). Both concepts emphasize that all dynamic behavior is generated within the boundary of a system.

[8] Contrarily to the previous section, we start here with the time dimension and therefore with the construction of the Cross-Delay Matrix. The reason for this is that the Cross-Effect Matrix, which will be introduced later, is constructed on the results of the CDM.

[9] The algorithm was introduced by Floyd (1962) and is explained in detail in Hürlimann (2009, p. 198). It is a simple algorithm which allows for the detection of the shortest path from node A to node B and solves the all-pairs shortest path problem on weighted-directed graphs. Compared to algorithms calculating all possible paths, the Floyd-Warshall algorithm is more economical, retaining the shortest path between two nodes once found. The algorithm has been implemented in a "Java Runtime Environment."

reaction at the receptor. However, we have to pay attention to the fact that there are many different paths from a source to a receptor, not only the shortest path. Therefore, the delay can be longer when other paths are taken into account, and feedback can thus be retarded. Nevertheless, the information provided by a CDM can be very important for decision makers seeking to determine when their intervention measures will begin to show returns.

Table 8: Cross-Delay Matrix: shortest path

delay from / to		1	2	3	4	5	6	7	8	9
1	Population	6	5	10	7	12	10	2	-	5
2	Birth	1	6	11	8	13	11	3	-	6
3	Death	1	6	11	8	13	11	3	-	6
4	Fertility rate	3	2	13	10	15	13	5	-	8
5	Death rate	3	8	2	10	15	13	5	-	8
6	Carrying capacity	10	9	14	7	12	15	2	-	10
7	Pop rel. to Cc	8	7	12	5	10	18	10	-	13
8	Regeneration of Cc	20	19	24	17	22	10	12	-	20
9	Degradation of Cc	15	14	19	12	17	5	7	-	15

Cross-Effect Matrix (CEM): Spread of effects

In this section, we aim to determine the size of the impact of variable x on variable y after "traveling" through the system. This should allow decision makers to anticipate the efficiency and effectiveness of their planned intervention measures.

In contrast to the previous section, where the delay accumulated en route from the source to the receiver, here the impulse can change in both directions. In other words, the impulse can strengthen but also diminish on its way to the receptor. To model the change in the impulse, we use the initial Cross-Impact Matrix from Table 3 and calculate all possible effects, following the shortest path using the results from the Cross-Delay Matrix introduced in the previous section. Now, in contrast to the computation of the active and passive sum of a variable, we incorporate real values for the impact strengths into our calculations.

The Cross-Effect Matrix (CEM) in Table 9 gives insight into all effects spreading from any variable to all reachable variables in a system following the shortest path. As an example, the impact of variable 9 (Degradation of Carrying Capacity)—which has been characterized as an intervention variable—on variable 1 (Population) will be described in Appendix A.

Table 9: Cross-Effect Matrix: Impulse following the shortest path

effect from	to	1	2	3	4	5	6	7	8	9
1	Population	0.67	0.67	0.67	-1.50	0.67	-1.00	1.00	-	0.67
2	Birth	1.00	0.67	0.67	-1.50	0.67	-1.00	1.00	-	0.67
3	Death	-1.00	-0.67	-0.67	1.50	-0.67	1.00	-1.00	-	-0.67
4	Fertility rate	0.67	0.67	0.44	-1.00	0.44	-0.67	0.67	-	0.44
5	Death rate	-0.67	-0.44	0.67	1.00	-0.44	0.67	-0.67	-	-0.44
6	Carrying capacity	1.00	1.00	-0.44	1.50	-0.67	-1.00	-1.00	-	0.67
7	Pop rel. to Cc	-1.00	-1.00	0.44	-1.50	0.67	1.00	-1.00	-	-0.67
8	Regeneration of Cc	0.67	0.67	-0.30	1.00	-0.44	0.67	-0.67	-	0.44
9	Degradation of Cc	-1.50	-1.50	0.67	-2.25	1.00	-1.50	1.50	-	-1.00

Combining effect and delay: How the system influences one variable

To visualize effect and time-span, we combine the data from the CDM (see Table 8) with data from the CEM (see Table 9), a process illustrated by the example. Determining how strongly and within what time span variable 1 (Population) is influenced by all of the other variables is done by extracting and combing the first columns of the CDM and the CEM. Using these values, the influences of the different variables on Population can be illustrated as shown in Figure 5.

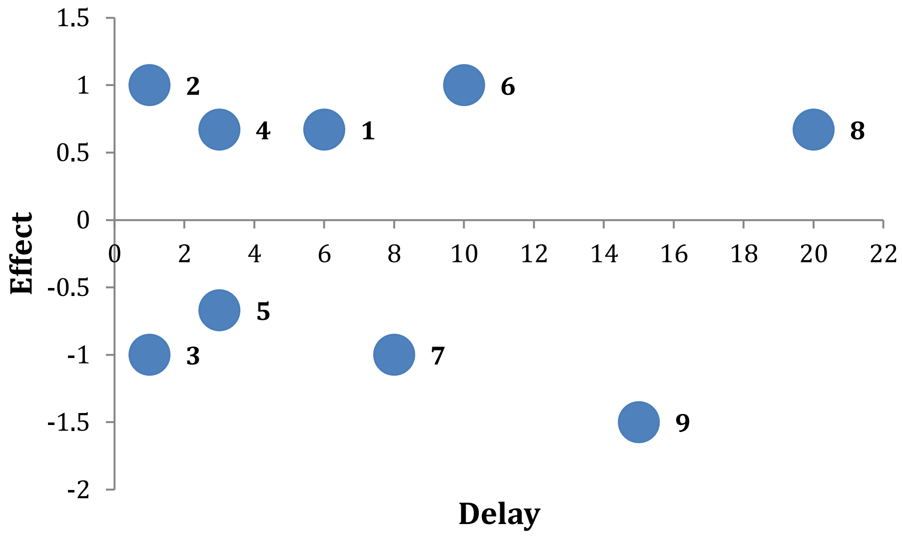

Figure 5: Incoming effects on the variable Population

The axis “Effect” can be divided into two parts. The part above zero shows the variables that have a positive impact on variable 1 (Population); the part below zero marks the variables that have a negative impact on Population. The areas between 0 and 1 or 0 and -1 indicate a sub-proportional change, whereas the influences of factors greater than 1 or less than -1 are over-proportional.

This portfolio delivers meaningful insights for decision makers when they have to decide which variables they should use for intervention. They can clearly distinguish between variables, seeing which are more appropriate for long-term adjustments of the system and which are more suited for short-time interventions.

Combining effect and delay: How one variable influences the system

There may be situations in which decision makers are not interested in finding the intervention point because they already know it. Rather, they are interested in gaining information regarding the consequences of an intervention. In this case, decision makers seek information on how a certain variable influences the others (with respect to delay and direction). Hence, information about the effect and the delay is needed. Here again, data from the CDM and the CEM can be combined by taking the values from the first rows of each matrix. All of the information extracted is visualized in Figure 6, representing how the variable 9 (Degradation of Carrying Capacity) influences any other reachable variable in the system.[10] This information reveals not only the strength of the impact of the chosen variable but also its direction and delay.

In sum, the combination of effect and delay in the last step enables us to obtain a holistic picture. If effect and delay are combined, one can easily ascertain whether a certain management strategy has the desired impact on a certain variable, and estimate the earliest time-point when such an impact can be expected. Hence, this portfolio can be very useful in discussing different management strategies or policies and their effects in the near and distant future.

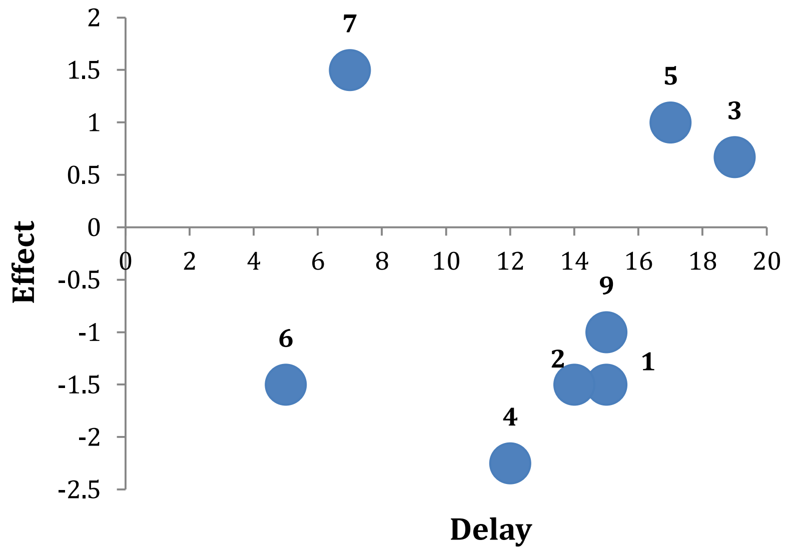

Figure 6: Outgoing effects of the variable Degradation of Carrying Capacity

[10] As variable 8 (Regeneration of Carrying Capacity) is only an input variable, it cannot be influenced by the variable Degradation of Carrying Capacity, and hence does not appear in Figure 6.

FEEDBACK STRUCTURE

The feedback structure plays a crucial role in system behavior. According to Sterman (2000, p. 12), most complex behaviors usually do not arise from the complexity of the components themselves but from the interactions (feedbacks) among the components. Feedback loops can be generally classified into two groups: positive (or self-reinforcing) and negative (or self-correcting) loops. Reinforcing feedback cycles have a predominantly destabilizing effect on a given system; they tend to boost or amplify every incoming impulse. In contrast to reinforcing feedback loops, self-correcting loops primarily equilibrate the system. If variable x is stimulated positively, the impulse will reverse polarity during the cycle and have a negative final impact on variable x (Sterman, 2000).

However, Cinquin and Demongeot (2002) highlight in their paper on positive and negative feedback in biological systems that "negative feedback can lead to expanding oscillations, a source of instability." They argue that negative feedback circuits exceeding a critical length of two can be destabilizing for a system. Cinquin and Demongeot point out that in long negative feedback loops "corrections to the variations of a variable can come too late, and give rise to an ever-expanding series of 'over-corrections,' a phenomenon commonly known as hunting."

In this paper we adopt Sterman's view on feedback structures. We assume that positive loops are a source of instability and negative loops a source of stability for a system. To learn more about the structure of our population growth model, we apply a search algorithm on feedback cycles (Hürlimann, 2009). We are particularly interested in finding answers to the following questions:

- How many different feedback loops exist in our population growth model?
- How many positive and negative feedback loops are there in the system?
- What are the consequences for network robustness if single variables are removed?

The latter bullet point is of special interest. What does it mean, in terms of feedback structures, if single variables are deleted? Which variables are indispensable to preserve stability for the entire system? We established a simple and comprehensive method for approaching these questions.[11] Table 10 summarizes the results of our feedback analysis.

Table 10: Feedback analysis

	neg. (-) feedbacks	pos. (+) feedbacks	total feedbacks	(-) / (+)
complete system	**6**	**1**	**7**	**6**

removed variable	variable number	remaining neg. (-) feedbacks	remaining pos. (+) feedbacks	total feedbacks	(-) / (+)	dependent neg. (-) feedbacks	dependent pos. (+) feedbacks	total dependent feedbacks	influence (%)
Population	1	1	0	1	∞	5	1	6	85.71%
Birth	2	4	0	4	∞	2	1	3	42.86%
Death	3	3	1	4	3	3	0	3	42.86%
Fertility rate	4	4	1	5	4	2	0	2	28.57%
Death rate	5	4	1	5	4	2	0	2	28.57%
Carrying capacity	6	3	1	4	3	3	0	3	42.86%
Pop rel. to Cc	7	2	1	3	2	4	0	4	57.14%
Regeneration of Cc	8	6	1	7	6	0	0	0	0.00%
Degradation of Cc	9	3	1	4	3	3	0	3	42.86%

The upper part of Table 10 reflects the situation if no variable is removed from the system. In total we have seven feedback loops split into six self-correcting and one self-reinforcing loop. This means our population growth model is dominated by negative feedback loops and tends to be stable. The lower part of Table 10 shows the results if each variable is taken out of the system. Obviously removal of variable 1 (Population) has the biggest impact on system stability, leaving just one negative feedback loop in the system. Consequently, variable 1 is an element of the other six feedback loops and has a high influence on the overall feedback structure of the system. In contrast, variable 8 (Regeneration of Carrying Capacity) has no influence at all on the global feedback structure of our population growth model. After deleting variable 7 (Population relative

[11] Our approach is based on the work done by Frederic Vester in 2002 (Vester, 2002, pp. 244-249)

to Carrying Capacity), three feedback loops remain in the system: two balancing and one reinforcing loop. It can be helpful to compare the ratio of remaining negative to positive feedback loops with the corresponding ratio in the complete system. For example, variable 7 has the largest impact on the predominance of self-correcting loops. Without this variable the ratio drops substantially from 6:1 in the complete system to 2:1 which could mean a considerable loss of stability for the system.

In this example, the results of the feedback analysis are obvious and there is no need for an algorithm to detect the feedback structure because the population growth model is so simple. However, if we are working with systems composed of many and/or highly interlinked variables, this feedback analysis will be very useful. In more complex systems it can also be reasonable to expand this feedback analysis by removing multiple variables simultaneously.[12]

IMPLICATIONS AND LIMITATIONS

The aim of this research is to support decision makers' efforts to address complex real-world problems. Because quantitative information is often missing, we focused on a qualitative approach from system theory. The methods presented in this article are based on matrices and should help decision makers to better understand the behavior of a system. The major advantages of the CIM and the CTM—the basis for our calculations—are that they can easily be completed by decision makers and do not require extensive quantitative modeling skills. Therefore, managers and decision makers are able to apply these tools in the strategic decision making process.

To gather feedback as to how this approach works, we have used the method during the last three years in our Executive MBA course. In this context, the approach has been applied in 29 case studies, dealing with complex management and socio-economic issues. The feedback and insights from these courses have been continuously used to improve and adapt the method. As a first, and hopefully not last, practical application to real-world problems, our approach has been applied in an expert study on the adjustment of the Swiss disability pension system (Bänziger & Gölz, 2011). This study

[12] Currently the authors of this paper are analyzing a terror network with our set of tools. We are testing efficient strategies to destabilize the terror network by removing bundles of variables.

has led to a stimulating policy discussion and has also found echo in press media (NZZ, 2012). Further practical applications in companies will also be considered in the near future.

Our experiences and the feedback of the executives with respect to the application of the presented tools are very positive. Although these methods are based on qualitative information, their additional insights into a system's behavior and the possibility of judging the appropriateness of intervention points and strategies have been greatly appreciated. An additional benefit of these tools is that they can be used as mental models to communicate complex issues among decision makers. Therefore, our method can contribute to the creation of a common understanding of complex problems in the decision making process. This can be fruitful in particular in cases when the involved stakeholders have different backgrounds or fields of expertise. Furthermore, our approach enables managers and other decision makers to go beyond the classical linear causality thinking, applying a broader system approach. This systemic thinking widens the perspective on complex issues incorporating side- and long-term effects, therefore supporting decision makers in developing sustainable solutions to these problems.

Our two-pronged approach, using first the CTM in combination with the CIM and the CDM in combination with the CEM and second applying feedback structure analysis, enhances the existing methods in the field of qualitative system analysis to an important extent. However, because it does not use a simulation technique, it is important to be aware that the results of the CDM and the CEM reflect only the first contact between two variables. To address this shortcoming, further tools need to be applied which include side effects from others paths aside from the shortest path. Our approach includes these path analyses, however the full coverage of these analyses would exceed the scope of this paper. Last, one critical remark must be made with respect to the interpretation of the different portfolios and matrices. Because qualitative information is used—at least in the CIM—roles or impacts of the different variables can only be interpreted relatively, not absolutely. This is an essential part of all qualitative analysis methods, in particular this approach: the system is the object of analysis, and all of the variables analyzed are part of the system. If another system or context is chosen, the system changes its structure, and different effects and time constraints can be observed.

Future research should deal with system archetypes. As system behavior is expected to be influenced to a large extent by system archetypes (Senge, 1990), identification and verification of such system archetypes can be useful for analysis of system behavior. Up to now system archetypes are mostly described qualitatively however we see great benefit for the SD community to model and simulate them in a semi-quantitative fashion.

APPENDIX A

Description of the population growth model

The model indicates that Population (1) is basically affected by the number of Births (2) and Deaths (3). Further, the size of Population relative to the carrying capacity (6) has an influence on the Fertility rate (4) and the health (Death rate 5) of the people. The density of a population leads to more stress and disease and negatively affects fertility. Fertility rate is the average number of children that would be born to a woman over her lifetime. Typically, a fertility rate of 2.1 is needed to stabilize a given population. The death (mortality) rate is typically expressed as the number of deaths per 1,000 people per year. Carrying capacity (7) is defined as the maximum population that can survive sustainably in a given environment. Carrying capacity can be consumed and degraded by the population but can also naturally recover. Carrying capacity is reduced if the population grows and more land is used for housing, roads and agricultural commodities.

As Figure 1 and Figure 2 show, variable 8 (regeneration of carrying capacity) influences the system from outside. It is a so-called “outside variable.” Variable 8 is only connected to one variable and thus does not show a high degree of cross-linking within the sample system.

Cross-Delay Matrix: When does an impulse arrive?

With respect to our example of population growth, the CDM provides some interesting information about when an impulse arrives at a receptor variable. For instance, a change in the Regeneration of the carrying capacity causes a reaction in Population with a delay of 20 units and in Deaths with a delay of 24 units. This result means that if Carrying capacity or the environment is regenerated, it takes quite a long time until changes are detectable within the system. Even though every change in Carrying capacity (environment) will have an impact on Population, it takes a rather long time before the impact becomes measurable.

Aside from information about the minimum delay between a change in a source variable and the reaction at the receptor variable, further information can be derived from a CDM. Obviously, the variable Regeneration of carrying capacity is not affected by the system. This is because this variable does not act as a receptor for any variable, as indicated in the CDM. Notably, this information can also be gained from the CTM. Then, the CDM in Table 8 demonstrates that there are paths from every variable (with the exception of Regeneration of carrying capacity) back to its own roots. This means that there are many feedback loops and that the system is highly cross-linked.

Cross-Effect Matrix: Spread of effects

Referring to the CEM in Table 9, the interrelation between variable 9 (Degradation of carrying capacity) and variable 1 (Population) bears discussion. If the environment has been used to a certain extent, the population will decrease over-proportionally, mainly due to environmental stress. If Carrying capacity diminishes, the Population relative to carrying capacity (7) increases, thus enhancing the stress factor for the population living in a certain environment and finally leading to a reduced Fertility rate (4), fewer Births (2) and more Deaths (3).

APPENDIX B

Floyd-Warshall algorithm

The Floyd-Warshall algorithm solves the all-pairs shortest path problem on weighted, directed graphs. Compared to the algorithm that searches for the shortest path by considering all possible paths this algorithm proceeds more economically. It memorizes the shortest path between two nodes once found. The algorithm is based on Floyd (1962, p. 345) and works on the principle of dynamic programming.

To function, the algorithm works with two matrices. The first one is an adjacency matrix called matrix A. This matrix represents the weighted, directed graph, and gives the distance between two vertices. The second matrix (B) retains the node one step before the targeted node of the shortest path known thus far. To begin, the algorithm proceeds as follows:

for i	=	1 to n
for all combinations of	:	x,y
except when x $\vee$ y	=	i do
when a(x,y)	>	a(x,i) + a(i,y) then
a(x,y)	=	a(x,i) + a(i,y)
b(x,y)	=	I
where		
n	:=	numbers of nodes
i,x,y	:=	Indicators
a(x,y)	$\in$	A
b(x,y)	$\in$	B

This algorithm has been implemented in a “Java Runtime Environment.”

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